Spatial Pricing and the Location of Processors in Agricultural Markets

Marten Graubner*, Alfons Balmann*, and Richard J. Sexton†

* Leibniz Institute of Agricultural Developement in Central and Eastern Europe (IAMO), Theodor-Lieser-Strasse 2, 06120 Halle (Saale), Germany; Contact author: Marten Graubner, phone: +49(0) 345 2928 320, fax: +49(0) 345 2928 399, Email: graubner@iamo.de

† University of California-Davis, One Shields Avenue, Davis (CA) 95616

Paper prepared for presentation at the EAAE 2011 Congress
Change and Uncertainty
Challenges for Agriculture,
Food and Natural Resources

August 30 to September 2, 2011
ETH Zurich, Zurich, Switzerland

Spatial Pricing and the Location of Processors in Agricultural Markets

Abstract

Spatially dispersed production and processing, endemic for most agricultural or renewable resource markets, causes oligopsonistic competition. The possibility and use of spatial price discrimination in these markets is well documented. It is also well known that the location of processors relative to competitors crucially affects the intensity of competition. However, insights regarding the relation between spatial price discrimination and the spatial differentiation of firms are barely present because the simultaneous investigation of these issues is often intractable analytically. We use computational economics to study these problems under a general theoretical framework. For instance, we show whether and under which conditions firms choose to differentiate their locations and/or price strategies. Results are consistent with observations in agricultural markets.

Keywords: spatial price competition, spatial differentiation, price discrimination, computational economics

1. Introduction

Non-negligible transport costs and spatially distributed production are important attributes of most agricultural commodities or renewable resources (e.g., forest, oilseeds or - with increasing importance - raw materials for bio-energy) and can cause oligopsonistic competition (Faminow and Benson, 1990; Löfgren, 1986). For instance, the location of new ethanol plants in the U.S. is an example of contemporary interest. New plants emerge in central locations as well as peripheral regions (Figure 1). While most plants are concentrated in regions with intensive corn production, entrants in these regions need to compete with established plants which cause input (corn) prices to increase in tendency (McNew and Griffith, 2005). Entrants in less intensified production regions (e.g., along the U.S. east cost) avoid this kind of price competition but may face higher procurement costs. Abstracting from different production densities and using homogeneous space instead, the only variable of interest are transport costs. Hence, the problem can be reduced to the trade-off between minimizing transport costs by central locations and relaxing price competition by peripheral locations (Beckmann and Thisse, 1986).

Location theory provides the framework to address these kinds of research questions. However, spatial competition for a homogeneous input is not necessarily characterized by the processors' locations solely. Instead, local market power enables spatial price discrimination to be used, and processors may choose among a variety of spatial price

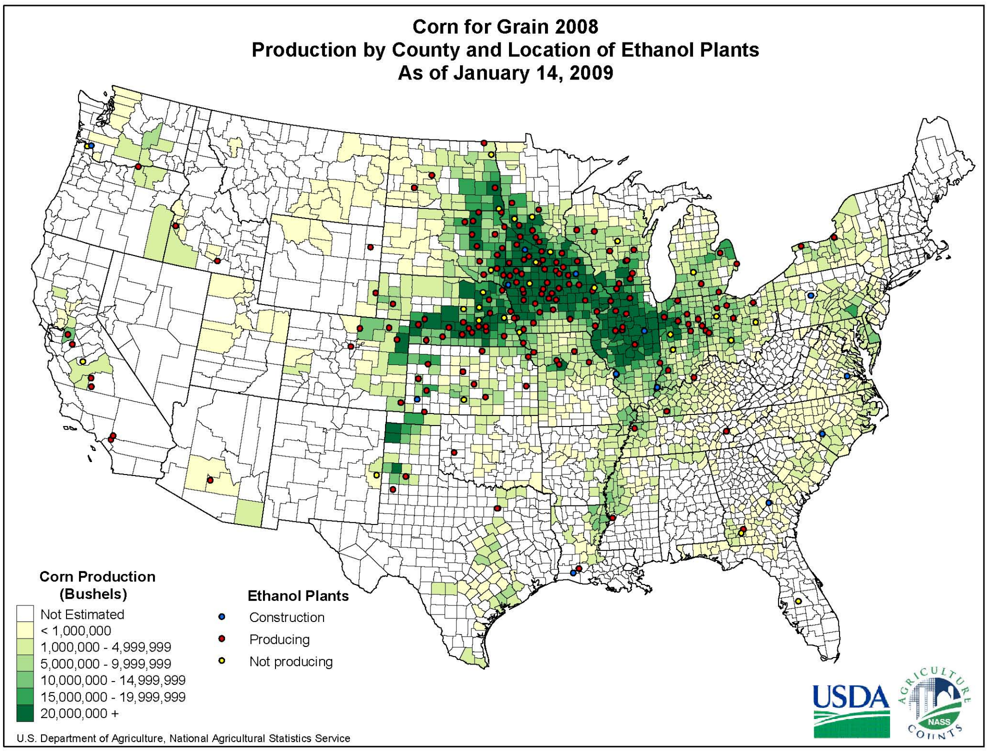

Figure 1. Location of ethanol plants in the U.S.

strategies which differ by the consideration of transport costs within the local price at the place of production (Löfgren, 1986).

Most models in spatial economics analyze either the firm's location or its price policy while the other is considered exogenous. However, a key variable that influences firms' decisions regarding the spatial price policy is the competitiveness of a market measured by the transport costs and distance to competitors (hereafter inter-firm distance) relative to the product's value (Thisse and Vives, 1988; Espinosa, 1992; Zhang and Sexton, 2001). The inter-firm distance, in turn, depends on, e.g., the number of firms in the region (Economides, 1993; Brenner, 2005) and/or the dimension of space (Tabuchi, 1994; Irmen and Thisse, 1998; Ansari et al., 1998).

To tackle the interdependencies of spatial pricing *and* location, i.e., between spatial price discrimination and spatial differentiation, we use a general theoretical model where competition is considered as interplay of the processors' locations and their spatial price policies. The latter are defined as linear price distance functions, i.e., the local price consists of the price at the processor's location (mill price) and the degree of freight absorption (spatial price discrimination). In this way, we represent a continuum of spatial price policies available to the firm including the three commonly studied strategies of spatial competition: free on board (FOB), uniform delivered (UD), and optimal discriminatory (OD) pricing.[1]

[1] Under UD pricing producers receive the same price irrespective of their location relative to the processor, while local prices differ exactly by transport costs in the case of FOB (or mill) pricing. Depending on the form of supply functions OD pricing involves partial freight absorption, i.e., local prices differ by an amount less than the actual transport costs.

Because we analyze a two-dimensional framework of multi-firm competition, analytical solutions cannot be obtained. Therefore, we take advantage of recent developments in the field of computational economics and use a simulation technique that is able to investigate spatial competition as a non-cooperative static game under relaxed competition. Particularly, we use an agent-based model for a spatial input market and identify the processors' decision (regarding location and price policy) by genetic algorithm learning (GA) of equilibrium strategies.

Among other characteristics, this model is able to incorporate multi-firm competition, two-dimensionality of the geographical region, as well as alternative elasticities of supply for the agricultural input. The investigation of an input market considering all these features and their combinations are extensions to existing literature. Hence, the method allows accounting for critical model assumptions, both in terms of their effect on the outcome and analytically tractability of the model. Instead of specifying the model to a particular market to explain certain observations, we conduct simulation experiments to analyze the impact of model parameters on equilibrium conditions. Consequently, the present paper can be understood as a first explorative approach towards understanding the interdependencies between location and pricing.

2. Theoretical Background

Let P denote the set of processors and S the set of suppliers (farmers) such that $P = \{p|\, p = 1, 2, \dots, i\}$ and $S = \{s|\, s = 1, 2, \dots, j\}$. Each of them occupies a location $L = (x, y)$ in two-dimensional space, with $x \in X = \left\{x \in \mathbb{R} \middle| 0 \le x \le x_{max}\right\}$, $y \in Y = \left\{y \in \mathbb{R} \middle| 0 \le y \le y_{max}\right\}$, and x_{max} and y_{max} being the exogenous size of the region. The maximum distance between two locations is $d_{max} = 1$ and other distances are scaled accordingly, i.e., $d_{LL'} \in [0, 1]$, with $d_{LL'} = \sqrt{(x_L - x_{L'})^2 + (y_L - y_{L'})^2} / \sqrt{x_{max}^2 + y_{max}^2}$. While $\mathbf{D} = (d_{sp})_{j \times i}$ is the distance matrix between suppliers and processors, the market's (average) inter-firm distance is:[2]

$$\overline{d} = \frac{1}{i} \left(\sum_i \left[\sum_p \frac{d_{pp'}}{i-1} \right] \right) \quad \forall p \text{ and } p \neq p'. \tag{1}$$

Processors are free to choose their location $L_p = (x_p, y_p)$, but suppliers are distributed in the region according to a density function $\tau(L) = 1$, i.e., there is exactly one supplier of the input at each point. The transport rate δ is constant. Transport costs between p and s are δd_{sp}. The local price $w_p(d_{sp})$ of firm p at point s is defined as a linear price distance function (Smithies, 1941a):

$$w_p(d_{sp}) = m_p - \alpha_p \delta d_{sp}. \tag{2}$$

While $\alpha = [0, 1]$ is a constant portion of the transport costs δd_{sp}, m_p is the mill price at the processor's location ($w_p(0) = m_p$). FOB pricing is characterized by $\alpha = 1$; there is no spatial price discrimination because local price differences reflect exactly the transport costs between different locations (Phlips, 1983). Conversely, if $\alpha = 0$,

[2] The formulation can be used for continuous and discrete space. In the simulation model, as used below, space is discrete in form of a grid of cells. There, the distance between two locations (two cells) is determined by the shortest distance from one cell's center to the other.

the processor uses UD pricing, i.e., there is an identical price over the market area of p. We denote $F = (m, \alpha)$ as the firm's spatial price strategy. We assume that suppliers are price takers and aim for the highest price. For any location $L = (x, y)$, the local price $w(L)$ is:

$$w(L) = \max \left\{ 0, m_p - \alpha_p \delta \sqrt{\frac{(x - x_p)^2 + (y - y_p)^2}{x_{max}^2 + y_{max}^2}} \right\} \quad \forall\, p \in P. \tag{3}$$

The input producer's supply function is:

$$q_s = q(w) = w(L)^{\epsilon} \quad \text{with } \epsilon \geq 0. \tag{4}$$

For the moment, we suppose $\epsilon = 1$ but vary this assumption later. Because the supplier's location is fixed, the local profit of an individual processor depends on its location L_p, i.e., the distance to the supplier's location d_{sp} and its price policy F_p. We denote γ_p as p's strategy, with $\gamma \in \Gamma$ and $\Gamma = (F, L) = (m, \alpha, x, y)$. The local profit depending on the distance to p can be written as:

$$\Pi_p(s) = (\varphi - w(d_{sp}) - t d_{sp}) q_s, \tag{5}$$

where φ is the net price of the finished good sold by the processor.[3] The processor only purchases the input from locations that yield positive local profits, i.e., $\varphi - w(d_{sp}) - \delta d_{sp} \geq 0$. Furthermore, the local price $w_p(d_{sp})$ has to be nonnegative, i.e., $m_p - \alpha_p \delta d_{sp} \geq 0$. Hence, there is a marginal location at distance R_p subject to p's price strategy F_p:

$$R(F_p) = \min \left\{ \left. \frac{m_p}{\alpha_p \delta} \right|_{\alpha > 0}, \left. \frac{\varphi - m_p}{(1 - \alpha_p)\delta} \right|_{\alpha < 1} \right\}. \tag{6}$$

All suppliers inside the market radius R_p based on L_p can contribute a positive amount to p's profit. We define this set of potential suppliers as:

$$C_p = \{c \in S |\, d_{cp} \leq R_p\}. \tag{7}$$

Whether c will deliver to p, also depends on the prices of the competitor at L_c. Consequently, the set of actual suppliers K_p is a subset of C_p, with:

$$K_p = \{k \in C_p |\, w_p(d_{kp}) \geq w(d_{kp'})\} \quad \forall\, p' \in P, p \neq p'. \tag{8}$$

Additionally, it is:

$$\begin{aligned} &K_p \subseteq C_p \subseteq S, \\ &K_p \cap K_p' = \emptyset \qquad \forall\ p,\ p' \in P,\ p \neq p', \quad \text{and} \\ &K \ \subseteq S \quad \text{with} \quad K = \sum_{p=1}^{i} K_p. \end{aligned} \tag{9}$$

[3] Using (2) to substitute for $w(\cdot)$ in (5) and differentiation with respect to m and α yields the optimal strategy of the monopsony: OD pricing with $F = (0.5, 0.5)$. However, OD pricing is mostly not optimal under non-cooperative competition.

As a result, we get p's profit by introducing (2) and (4) into (5) as sum over K_p:

$$\Pi_p(\gamma_p, \boldsymbol{\gamma}_{\mathbf{p}'}) = \sum_k [\varphi - m_p - (1-\alpha)\delta d_{kp}](m_p - \alpha\delta d_{kp}), \tag{10}$$

where $\boldsymbol{\gamma}_{\mathbf{p}'}$ is a vector of the competitors' strategies.

3. Simulation Model

To analyze this system, i.e., to maximize (10) for each processor subject to its strategy and the strategies of competitors, we use an agent-based model (ABM). The two types of economic actors considered in the model are processors and suppliers of an homogeneous agricultural raw product and their respective objective functions are (10) and (4). Suppliers are price taker, but processors exhibit (local) market power. The optimization rule (4) of input producers is to select the highest price at the own location and set quantity accordingly, and it can easily be implemented by a computer program. The decision rule of every processor is more complex. The processor's payoff depends on the competitors' strategies according to (10). In this respect, it is well known that payoffs are discontinuous in the competitor's strategy and pure strategy equilibria fail to exist, e.g., if firms locate too close to each other and use FOB pricing (D'Aspremont et al., 1979) or in the case of competition under UD pricing (Beckmann, 1973; Kats and Thisse, 1989). Moreover, the two-dimensional and multi-player framework causes first order conditions of (10) to be polynomials of high degrees and analytical (closed form) solutions do not exist.[4] Therefore, to identify (close to) equilibrium strategies in our general theoretical framework necessitates a powerful and flexible numerical tool. We apply genetic algorithms (GA), which repeatedly have proven to be successful in identifying equilibrium strategies in complex games.[5]

A GA is a stochastic heuristic search method to find optimal or close-to-optimal solutions in large decision or strategy spaces (Mitchell, 1996; Goldberg, 1989). In analogy to the biological evolution, the principle of GA is based on the survival of the fittest (Dawid, 1999). During optimization, GA allows for the creation of new, potentially superior solutions, which makes GA efficient and robust, i.e., it minimizes both the dependency on the initial conditions and makes GA optimization less vulnerable for local optima lock-in. While GAs have successfully been used over a broad range of disciplines (Foster, 2001), economic applications to identify equilibria in games in general and strategic market situations in specific include Axelrod (1987), Arifovic (1994), Price (1997), Vallée and Başar (1999), Balmann and Happe (2001), and Alemdar and Sirakaya (2003). A more detailed description of the GA and an illustration of its abilities and precision are given by means of a simple spatial competition example

[4] For instance, Tabuchi (1994) uses a conversion of the uniform distribution of consumers in two-dimensional space to a non-uniform distribution in one-dimensional space, which is not possible for more than two firms. A similar difficulty regarding the number of firms affects the analysis of Brenner (2005). As a result, he uses numerical methods to analyze the location of more than three firms in one-dimensional space. Osborne and Pitchik (1987), who characterize mixed strategy equilibria in the original Hotelling game, as well as Ansari et al. (1998), who extend the Hotelling model to two- or multi-dimensional space, also use numerical methods.

[5] To validate the simulation model in a spatial competition framework, we also used results derived from theoretical models that include Norman (1981); Kats (1995); Hinloopen and van Marrewijk (1999); Zhang and Sexton (2001). The simulation was able to recapitulate these results with high precision.

in the supplementary material to this paper.[6] In the next section, experiments for different spatial competition scenarios are presented. Thereby, the agent-based approach provides an instrument to grasp the spatial dimension of a market and the interaction among spatially differentiated players within it. Space is represented by a grid of cells and locations are accessible by x-y coordinates. In order to exclude border effects, it is feasible to wrap the space by constructing a torus or to analyze the influences of border effects by using the simple, quadratic plane. In either case, the normalization $d_{max} = 1$ is maintained. Each cell can be occupied by a number of agents but only by one producer exactly. This represents the discrete form of the density function $\tau(L) = 1$.

Because the GA simulation is based on a stochastic process, we get a distribution for each of the decision variables. Therefore, we separately present a simulation's outcome by density plots of location and price policy. In this way, we can easily link the respective two decision parameters: the location in space via a x-y plot and the price strategy parameters by a m-α plot. The price policy parameters are discrete with increments of 10^{-3} to 10^{-2}. Due to the introduced suppliers' distribution function and considerations with respect to processing time, the region, whether or not modeled as torus, is discrete in space such that $X = Y = \{0, 1, ..., 20\}$. Consequently, there are 400 equidistant points and each of these points is occupied by one farmer. The processors, however, can locate at any of those 400 points. Within the density plots, the frequency of variable combinations (either location or price policy) is illustrated by color. The lighter a point within the x-y or m-α plane, the more frequent the parameter combination was observed as the outcome of the game. Although partly caused by the stochastic nature of the algorithm, we may interpret the variability of the results as evidence whether or not pure-strategy equilibria in location, price policy or both exists. However, it is not the objective of the paper to characterize equilibria whether or not in pure or mixed strategies. Instead, we doubt that this is feasible in all presented cases.

4. Simulation Experiments and Results

The outcome of spatial competition models is very sensitive with respect to the underlying assumptions. The objective of the following simulation experiments is to analyze some of the critical assumptions (both in terms of the outcome and tractability of the models) in order to extend the understanding of spatial competition. Particularly, we are interested in the relation between location and spatial price discrimination subject to transport costs (δ), the number of processors (i), the nature of space, and the price elasticity of supply functions for the input suppliers. The first two points directly influence the degree of spatial competition but, as we will see, in a surprisingly different manner. Note that we set the product price $\varphi = 1$ via normalization. Hence, normalized transport costs $t = \delta/\varphi$ is a relative measure of market competitiveness (Zhang and Sexton, 2001; Mérel and Sexton, 2010). For instance, $t = 0$ yields the classical Bertrand price competition, while sufficiently high transport costs may lead to spatially separated monopsonies if processors do not choose to locate at the same place. Hence, the markets competitiveness decreases with the importance of space $t\overline{d}$

[6] This and other examples as well as a more detailed documentation of the simulation model can be provided by the corresponding author upon request.

Table 1. Specifications of the simulation experiments. Unlisted parameters are set according to Section 2.

Parameter	Simulations			
	Duopsony	Oligopsony	Unbounded Space	Inelastic supply
i	2	$3,\ldots,6$	$2,\ldots,6$	$2,\ldots,6$
j	400	400	400	400
φ	1.0	1.0	1.0	1.0
t	$0.0,\ldots,4.0$	2.0	2.0	2.0
x_{max}, y_{max}	20	20	20	20
e	1.0	1.0	1.0	0.0
space	plane	plane	torus	plane
NoG	6250	3750	3750	3750

i = number of processors, j = number of suppliers, t = normalized transport rate, φ = price of the processed good, x_{max}, y_{max} = size of region, e = price elasticity of supply, NoG = number of analyzed games.

because t, which is exogenous, increases and/or because processors decide to locate more distant from each other.

In the next sections, simulations are conducted for several selected values of t and i. In contrast, the supply function and the nature of space are analyzed in two states only. Regarding the latter, we compare a finite two-dimensional plane and a finite space without borders, i.e., a torus. Furthermore, we estimate the effects of the supply elasticity by two special cases: unit-elastic supply ($\epsilon = 1$) and unit-supply ($\epsilon = 0$). Table 1 summarizes the specification of the simulations.

4.1. Duopsony

In the first experiments, we investigate processors' decisions regarding the location and the spatial price policy in duopsony depending on the degree of competition. Figure 2 shows the outcome of the simulations for selected values of transport costs.

The first row of density plots in Figure 2 represents the location of the two processing firms. The lighter the color of a cell the more frequent the location was chosen during the simulation. The frequency is scaled, i.e., a white colored cell indicates the maximum while a black one corresponds to zero. Accordingly, the second row highlights the frequency of the strategy parameter combinations.

From the left to the right, transport costs (importance of space) increase(s), i.e., competition decreases. If $t = 0$, we observe a diffuse location distribution. Conversely, we notice two location equilibria for high transport costs (e.g., $t = 4.0$). In the first case, the distance between firms does not matter, while the latter case is the two-dimensional version of the "touching equilibrium" case as studied in Economides (1984) or Hinloopen and van Marrewijk (1999). Instead of location at the quartiles, as in the one-dimensional touching equilibrium, processors locate at the center of the opposite region's quadrants to act as locally separated monopsonists, i.e., if firm A

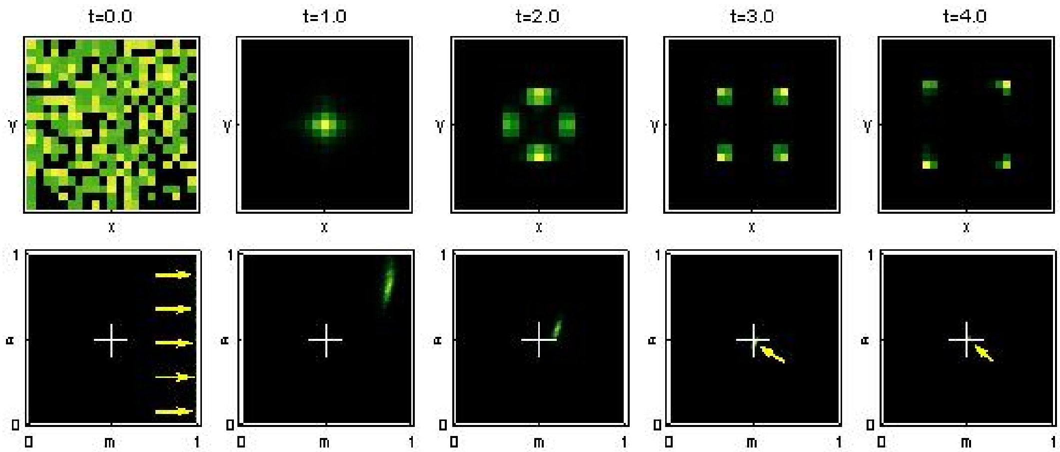

Figure 2. Location (above) and pricing (below) of the duopsony for selected values of t. Narrow distributions are highlighted by arrows, as in the case of $t = 0.0$ where $m \approx 1$, while α is uniformly distributed over [0,1].

locates in lower left, B locates in upper right, or if A locates in upper left, B locates in lower right. In either case, the market radii of both firms touch at the market center.

Between the two limit cases of $t = 0$ (perfect competition) and $t \geq 4$ (local monopsony), spatial differentiation increases with increasing importance of space (decreasing market competitiveness). While firms locate at the center of the market if competition is fierce (see the second plot in the first row of Figure 2, $t = 1$), the distance between both firms increases once transport costs become more important. Additionally, we observe a relation between the the second part of the firms' strategy, the spatial price policy, and the intensity of spatial competition. This is shown in the second row of Figure 2. Again, the first plot represents $t = 0$. In this case, α does not influence local prices and is not essential for profit maximization. The observed uniform distribution of α at the right edge of the figure (marked by the arrows in $t = 0$) is caused by the random initialization of the decision variables within the simulations. As expected, the optimal strategy corresponds to Bertrand competition with $m = \varphi = 1$.

If $t > 0$ but is sufficiently low, e.g., $t = 1$, high mill prices accompanied with high α values (low price discrimination) are observed, i.e., processors use close to FOB pricing. With increasing transport costs and spatial differentiation, we observe increasing spatial price discrimination but decreasing mill prices. If $t \geq 4$, both firms can operate as local monopsonists given the respective choice of location and use the profit maximizing OD price regime with $F = (m, \alpha) = (0.5, 0.5)$.

4.2. Oligopsony

The transport costs, measured by t, are one important parameter influencing competition in spatial markets. In the previous section, lower values for t increase the competitive pressure on processors because the relation between the importance of space $t\bar{d}$ and the value of the finished good (which was set to one) decreases. In this section, we discuss the case of increasing competition due to an increasing number of processors i. More firms diminish the (average) inter-firm distance and appear like a reduction of t. However, the number of competitors crucially affects the market

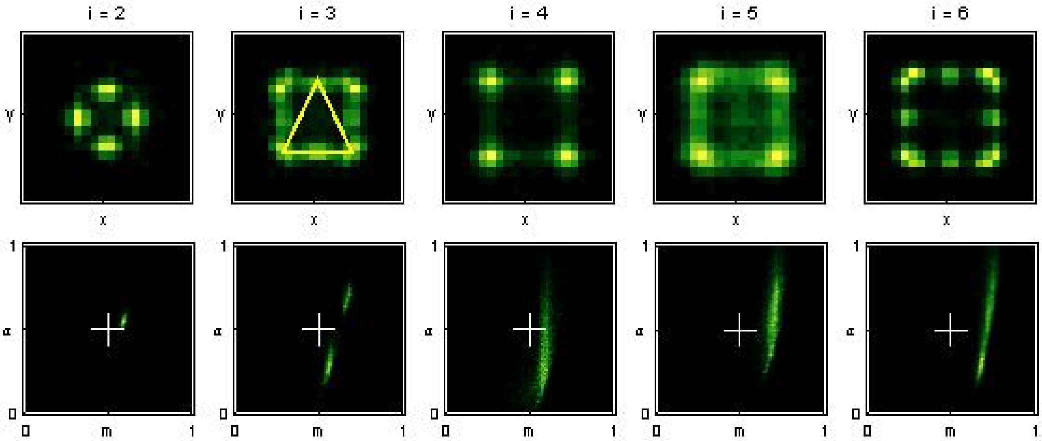

Figure 3. Location (top) and pricing (bottom) of the oligopsony. The case of two to six firms. The first row illustrates the firms' locations, while the second row highlights the frequency of the price strategy parameters.

structure such that some firms may face competition in more than one direction while others do not.

Simulations are conducted for three to six firms. In each scenario, $t = 2$ to highlight the pure influence of i. Figure 3 shows the outcomes for the location-price-policy game. The case of two firms is pictured to compare the duopsony with the oligopsony outcomes. Again, the upper row provides information where the firms locate. Obviously, independent of i, the square seems to be the general location pattern. Yet, depending on i, firms locate at the angles, on the (middle of) edges, or even close to the market center. These cases are discussed below. The robustness of the general location pattern, however, is not surprising because the market region is modeled as square. This is particularly intuitive in the case of four firms.

In the case of $i = 3$, the simulation data reveal that the locations of the three firms coincide with corners of a triangle as depicted yellow in the location plot. By the rotation of this triangle, we obtain four typical location equilibria in total. Thereby, two firms locate at neighboring angles of the general location pattern. We denote these locations as L_a. The third firm locates midpoint on the opposite segment of the general location pattern and we denote this location L_e. Considering the firm's price policy, depicted in the lower row of Figure 3, we find that a firm located at L_e uses a price strategy $F_e = (m_e, \alpha_e)$ which consists of m-α combinations from the first quadrant (upper left) of the price strategy plot. These strategies are characterized by both high m and α. Conversely, the lower right quadrant's policies feature higher price discrimination (lower α values) and correspondingly lower mill prices. These strategies, which we denote F_a, are employed by firms located at L_a. These results are remarkable because they illustrate the relation between pricing and location as well as make the potential of agent-based modeling apparent. We observe not only heterogeneity in location but also differentiated price strategies.

The scenarios with four and five firms show a high variability but no clear differentiation of price strategies. While strategies for $i = 4$ are mostly located in the fourth quadrant (high price discrimination), the m-a combinations are spread over the first and fourth quadrant for $i = 5$. If we plot the corresponding α values of the latter case pursuant to the coordinates, we notice that locations in the center of the square pattern are linked to high price discrimination (low α-values). Centrally located firms face fierce competition in each direction, while peripherally located firms have more local market power. These results are in line with Economides (1984) or Brenner (2005). The authors observe a U-shaped price structure in the FOB pricing oligopoly with a linear market, i.e., FOB mill prices are high at the market's edge and decrease with decreasing distance to the market's center. However, our results highlight market power of peripheral firms by lower price discrimination.

Although of less magnitude, we also observe differentiation of price strategies for $i = 6$. Frequency peaks are in the first and fourth quadrant of the price policy plot of Figure 3. Thereby, four firms occupy the angles of the square, i.e, the general location pattern, and two firms are oppositely located at the margin. The latter face competition in two directions and use the strategies of the fourth quadrant.

4.3. Unbounded Space

Most of the one-dimensional models of location or product differentiation are based on Hotelling's finite line market with boundaries (Economides, 1993; Ansari et al., 1998; Brenner, 2005). This is an intuitive assumption because there is almost always a minimum and maximum of a quality or some kind of market border. However, border effects may not only cause analytical difficulties but may also lead to qualitative different model predictions. For instance, Salop (1979) and Kats (1995) investigate a circular market framework. While Salop (1979) assumes symmetric location equilibria, Kats (1995) proofs their existence. Under a two-dimensional framework, we use a torus where $(x, y) = (\{0, 1, \ldots, x_{max}\}, \{0, 1, \ldots, y_{max}\})$ and locations with the coordinates $(x, 0)$ and $(0, y)$ are direct neighbors of (x, y_{max}) and (x_{max}, y), respectively. Even though this construct is a strong abstraction, particularly with respect to spatial markets, it facilitates the analysis of spatial competition when firms always have a neighbor in each direction.

Figure 4 shows the outcome for the finite market without boundaries. Note that the location of one firm is fixed at $(x, y) = (0, y_{max})$ to make the location pattern visible.[7] In the case of two firms, we observe maximum differentiation and OD pricing. While the location is robust over t, the price strategy is caused by $t = 2$. The maximum distance in the market is $d_{max} = 1$.[8] Firms can act as locally separated monopsonies if $\bar{d}t \geq 2$ because it must hold that $4R^* \geq d_{max}$, and R^* is the monopsonistic market radius given by a price policy $F = (1/2, 1/2)$ and (6). We note that there is a significant difference between this case and the outcome of $t = 2$ in Figure 2. In the bounded market, the maximum distance is between two opposing corners. Accordingly, if the firms locate inside the market $\bar{d} < d_{max}$, and to have $t\bar{d} = 2$ requires, e.g., location at the quartiles of a diagonal and $t = 4$. Consequently, we can compare the case of $t = 2$ in this section with the outcome of $t = 4$ of Figure 2.

---

7 If we consider the torus (or a circular market), instead of the actual location the distance between the firms is crucial. As a result, if there is one location equilibrium, there is an infinite number of location equilibria because the addition of the same vector to each of the firms' locations yields another location equilibrium.

8 Note that the maximum distance in the market under the torus is, e.g., between the market center and a corner.

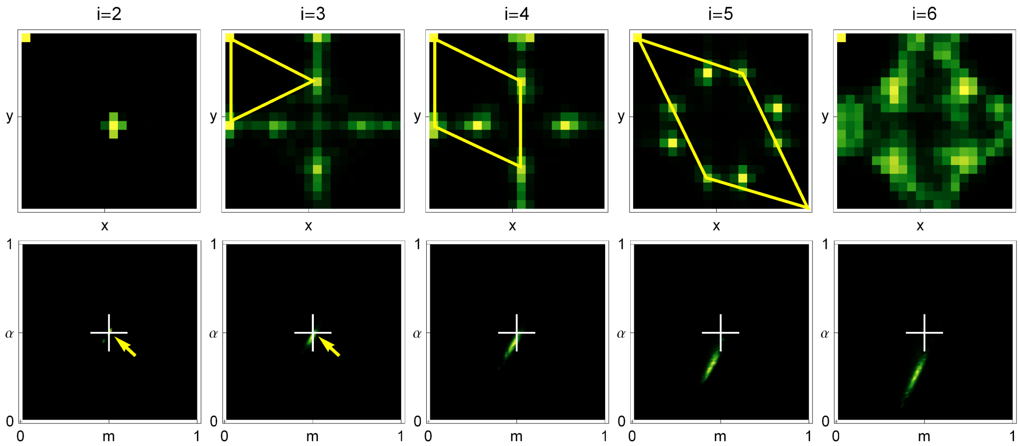

Figure 4. Location and pricing of the oligopsony in unbounded space (torus). In the location figures: cells at the upper edge are direct neighbors of cells at the lower edge. The same is true for the left and right edge. The location of one firm is fixed at the upper left corner with $(x, y) = (0, y_{max})$. In cases of multiple location equilibria, typical constellations are exemplified.

The next three figures ($i = 3, \ldots, 5$) show increasing competition given a constant transport rate but an increasing number of competitors. The distribution of the location parameters highlight the firms' attempt to locate equidistantly.[9] We can identify multiple location equilibria in almost all figures. The location of the firms is illustrated by geometrical forms as highlighted yellow in the particular scenarios but also by the rotation or shift of these forms. If $i = 5$, the firms' locations are on two parallel straight lines. Note that the upper left and lower right corner represent one location (the same firm). The algorithm is not able to find a stable location pattern if $i > 5$. Considering the price strategies, we identify increasing spatial price discrimination with increasing competition. In contrast to bounded space, price strategies that are characterized by high α values are not observed.

The identification of increasing price discrimination with increasing competition is in sharp contrast to the results in the previous section. This clearly highlights how the construction of space influences the model's outcome. The implications regarding the spatial analysis as well as the investigation of product differentiation cannot be neglected. In this regard, the present study is a generalization of Economides (1993) or Brenner (2005) who attribute border effects significant impact on results in the case of one-dimensional space under FOB pricing. Conversely, in almost all models of spatial price competition, addressing the question regarding the optimal price policy under competition, a line market is assumed where two firms are located at the end points (Kats and Thisse, 1989; Espinosa, 1992; Zhang and Sexton, 2001). While this structure is consistent with circular markets as studied by Salop (1979) or Kats (1995), the presence of some kind of border or limit might be an intuitive feature of spatial markets as well as markets of differentiated products. Nevertheless, both types of space might be appropriate for different questions and particular for different markets,

[9] Slight deviations from equidistant locations are caused by the discrete nature of the space. To relocate, a firm has to increment either its x or y variable at least by one.

but one has to be aware that one or the other structure significantly influences the prediction of the model.

4.4. Perfectly Inelastic Supply

If supply is elastic, producers can mitigate a potentially negative effect of higher local input prices on a firm's profit by rising local supply. This supply effect is not present under perfectly inelastic supply functions, which significantly alters the results. If we consider unit-supply within the simulation model where the producer's reservation price is zero, we identify a typical location pattern in form of a square but less distinctive relative to previous experiments. We can also observe that prices (price discrimination) increase (decreases) in tendency with increasing competition, i.e., with an increasing number of competitors. Beside these observations, however, we are not able to identify location equilibria in this setting. Additionally, price strategies are distributed over a wide range of m-α combinations. Both results are not surprising. If supply is perfectly inelastic, it is well known that equilibria in pure strategies do not exist (D'Aspremont et al., 1979). However, the observation of a wide variety of price and location strategies also supports the conclusion that price discrimination crucially depends on spatial differentiation, i.e., the relative location of competitors.

5. Summary and Discussion

The main findings of the simulations are summarized by Table 2. For instance, we observe increasing (decreasing) spatial price discrimination (α-values) with increasing normalized transport costs under duopsony as well as an increasing number of competitors under oligopsony. However, the competitiveness of the market differs in both cases, i.e., it increases with i but decreases with t.

For comparable assumptions, our results are supported by existing theoretical investigations of partial aspects of the competition model as presented in this paper. This validates the model. For example, Smithies (1941b) and Eaton (1972) show that non-cooperative competition and elastic demand yields incentives for (close to) central locations in the Hotelling model; Zhang and Sexton (2001) also yield mixed pricing in equilibrium over some range of spatial differentiation in the duopsony; Economides (1993) and Brenner (2005) also show that depending on location, some firms may exhibit relatively higher local market power; and, as we observe maximum differentiation in unbounded two-dimensional space, Kats (1995) gets this result for circular markets. Additionally, there is empirical evidence. For instance, the survey of Greenhut (1981) shows a variety of pricing in reality and we observe most of them in the simulations.

In general, we can explain our results with different effects caused by the flexible adaptation of linear price strategies and the endogenous choice of location. Both represents a significant extension to previous price-location models. For instance, consider the case of close to minimum differentiation under duopsony ($t = 1$). The observed price strategy ensures high prices at the market border between both processors. This competitive effect protects proximate locations from overbidding by the competitor. At the same time, high local prices at proximate locations facilitate high supply effects where it is most profitable (due to low transport costs) and low price discrimination secures large market areas (market area effect) under high mill prices because suppli-

Table 2. Outcome of the simulation experiments.

Variable:	Duopsony transport costs	Oligopsony number of firms	Unbounded space number of firms	Inelastic supply number of firms
m	▼	☐	▼	▲
α	▼	☐	▼	▲
$\overline{d}$	▲	▼	▼	▼

m = processor's mill price at its location, α = share of transport costs in local prices, β = degree of spatial price discrimination, $\overline{d}$ = average distance between processors, ▼ = decreasing, ▲ = increasing, ☐ = indeterminate.

ers bear most of the transport costs. Consequently, the processor efficiently competes against the proximate rival and accesses remote locations in the direction where no other processor is located. We call these regions the hinterland of a processor.

Another example is the case of the oligopsony where some firms use higher price discriminating strategies than others (e.g., if $i = 3$ or $i = 6$). Under the chosen locations, these processors face fierce competition in more than one direction. Therefore, the competitive effect of pricing is the driving force. Firms discriminate against proximate suppliers to set higher prices at more distant locations. Conversely, if processors occupy a location with significant hinterland, they face less intense competition. The price strategy decision of these firms to opt for less price discrimination is driven by the market area effect.

The presented simulation experiments cover a wide range of observations in agricultural markets. For instance, markets for raw milk, meat packing, or fruit and vegetables feature spatially distributed production and processing as well as high price discrimination (cf. Durham et al., 1996; Alvarez et al., 2000; Graubner et al., 2011). Our results under oligopsony are consistent with these observations. Equally, we observe FOB pricing in markets where more than one processor locates at the same location as in the case of grain delivered to harbors, the shipment of fresh produce to traditional terminal markets (e.g., Sexton et al., 1991) or to one of multiple packing houses located in close proximity to intense growing regions (e.g., Cho, 2004). Gallagher et al. (2005) identify different pricing strategies of ethanol plants and our results can explain this observation with the intensity of local competition.

6. Conclusion

We investigate spatial competition from an input market perspective because transport costs and spatial distribution of supply and demand are key aspects for many markets of agricultural products and renewable resources. Unlike previous studies, we consider spatial differentiation (location of firms) and spatial price discrimination (spatial pricing of firms) endogenous. Our approach accommodates a much more general depiction of spatial competition than prior work, including two-dimensional spatial markets, competition among multiple firms, and elastic input supply functions. To surmount the problem of analytical intractability, we use a computational approach by combining agent-based modeling with genetic algorithms.

While results considerably differ from previous studies, they are widely consistent with what we observe in agricultural markets including spatially dispersed production and processing and the prevalence of spatial price discrimination in processor's pricing strategies. The particular aim of the paper is to provide a first investigation of what is or could be possible and where might it be helpful. We showed that there are a number of conditions which need to be considered, and often we do not even know how alternative formulations of these assumptions or their combination affect the prediction of a spatial competition model. Important issues of spatial economics are the firm's location and the nature of price competition in space. We addressed how the one affects the other subject to critical model assumptions. Our results clearly highlight that spatial competition models need to be carefully specified.

References

Alemdar, N., Sirakaya, S., 2003. On-line computation of Stackelberg equilibria with synchronous parallel genetic algorithms. Journal of Economic Dynamics and Control 27 (8), 1503–1515.

Alvarez, A. M., Fidalgo, E. G., Sexton, R. J., Zhang, M., 2000. Oligopsony power with uniform spatial pricing: Theory and application to milk processing in Spain. European Review of Agricultural Economics 27 (3), 347–364.

Ansari, A., Economides, N., Steckel, J., 1998. The max-min-min principle of product differentiation. Journal of Regional Science 38 (2), 207–230.

Arifovic, J., 1994. Genetic algorithm learning and the cobweb model. Journal of Economic Dynamics and Control 18 (1), 3–28.

Axelrod, R., 1987. The evolution of strategies in the iterated prisoner's dilemma. In: Davis, L. (Ed.), Genetic Algorithms and Simulated Annealing. Pitman, London.

Balmann, A., Happe, K., 2001. Applying parallel genetic algorithms to economic problems: The case of agricultural land markets. In: Johnston, R., Shriver, A. (Eds.), Microbehavior and Macroresults: Proceedings of IIFET 2000. International Institute of Fisheries Economics and Trade, Oregon State University, Corvallis (OR).

Beckmann, M. J., 1973. Spatial oligopoly as a noncooperative game. International Journal of Game Theory 2 (1), 263–268.

Beckmann, M. J., Thisse, J.-F., 1986. The location of production activities. In: Nijkamp, P. (Ed.), Handbook of Regional and Urban Economics. Vol. 1. Elsevier Science, Amsterdam.

Brenner, S., 2005. Hotelling games with three, four and more players. Journal of Regional Science 45 (4), 851–864.

Cho, S., 2004. An economic analysis of the washington apple industry, ph.D. Dissertation, Washington State University.

D'Aspremont, C., Gabszewicz, J. J., Thisse, J.-F., 1979. On Hotellings 'Stability in Competition'. Econometrica 47 (5), 1145–1150.

Dawid, H., 1999. Adaptive Learning by Genetic Algorithms, 2nd Edition. Springer, Berlin.

Durham, C. A., Sexton, R. J., Song, J. H., 1996. Spatial competition, uniform pricing and transportation efficiency in the California processing tomato industry. American Journal of Agricultural Economics 78 (1), 115–125.

Eaton, B. C., 1972. Spatial competition revisited. Canadian Journal of Economics 5 (2), 268–278.

Economides, N., 1984. The principle of minimum differentiation revisited. European Economic Review 24 (3), 345–368.

Economides, N., 1993. Hotelling's 'Main Street' with more than two competitors. Journal of Regional Science 33 (3), 303–319.

Espinosa, M. P., 1992. Delivered pricing, fob pricing, and collusion in spatial markets. Rand Journal of Economics 23 (1), 64–85.

Faminow, M. D., Benson, B. L., 1990. Integration of spatial markets. American Journal of Agricultural Economics 72 (1), 49–62.

Foster, J. A., 2001. Evolutionary computation. Nature: Reviews Genetics 2 (6), 428–436.

Gallagher, P., Wisner, R., Brubacker, H., 2005. Price relationships in processors' input market areas: Testing theories for corn prices near ethanol plants. Canadian Journal of Agricultural Economics 53 (2-3), 117–139.

Goldberg, D. E., 1989. Genetic Algorithm in Search, Optimization and Machine Learning. Addison-Wesley, Reading (MA).

Graubner, M., Koller, I., Salhofer, K., Balmann, A., 2011. Cooperative versus non-cooperative spatial competition for milk. European Review of Agricultural Economics 38 (1), in press.

Greenhut, M. L., 1981. Spatial pricing in the United States, West Germany and Japan. Economica, New Series 48 (189), 79–86.

Hinloopen, J., van Marrewijk, C., 1999. On the limits and possibilities of the principle of minimum differentiation. International Journal of Industrial Organization 17 (5), 735–750.

Irmen, A., Thisse, J.-F., 1998. Competition in multi-characteristics space: Hotelling was almost right. Journal of Economic Theory 78 (1), 76–102.

Kats, A., 1995. More on Hotelling's stability in competition. International Journal of Industrial Organization 13 (1), 89–93.

Kats, A., Thisse, J.-F., 1989. Spatial oligopolies with uniform delivered pricing. Core Discussion Paper 8903, Université catholique de Lovain, Louvain-la-Neuve.

Löfgren, K.-G., 1986. The spatial monopsony: A theoretical analysis. Journal of Regional Science 26 (4), 707–730.

McNew, K., Griffith, D., 2005. Measuring the impact of ethanol plants on local grain prices. Review of Agricultural Economics 27 (2), 164–180.

Mérel, P. R., Sexton, R. J., 2010. Kinked-demand equilibria and weak duopoly in the Hotelling model of horizontal differentiation. B.E. Journal of Theoretical Economics 10 (1), contributions, Article 12.

Mitchell, M., 1996. An Introduction to Genetic Algorithm. MIT Press, Cambridge (MA).

Norman, G., 1981. Spatial competition and spatial price discrimination. Review of Economic Studies 48 (1), 91–111.

Osborne, M. J., Pitchik, C., 1987. Equilibrium in Hotelling's model of spatial competition. Econometrica 55 (4), 911–922.

Phlips, L., 1983. The Economics of Price Discrimination. Cambridge University Press, Cambridge.

Price, T. C., 1997. Using co-evolutionary programming to simulate strategic behaviour in markets. Journal of Evolutionary Economics 7 (3), 219–254.

Salop, S. C., 1979. Monopolistic competition with outside goods. Bell Journal of Economics 10 (1), 141–156.

Sexton, R. J., Kling, C. L., Carman, H. F., 1991. Market integration, efficiency of arbitrage, and imperfect competition: Methodology and application to U.S. celery. American Journal of Agricultural Economics 73 (3), 568–580.

Smithies, A., 1941a. Monopolistic price policy in a spatial market. Econometrica 9 (1), 63–73.

Smithies, A., 1941b. Optimum location in spatial competition. Journal of Political Economy 49 (3), 423–439.

Tabuchi, T., 1994. Two-stage two-dimensional spatial competition between firms. Regional Science and Urban Economics 24 (2), 207–227.

Thisse, J.-F., Vives, X., 1988. On the strategic choice of spatial price policy. American Economic Review 78 (1), 122–137.

Vallée, T., Başar, T., 1999. Off-line computation of Stackelberg solutions with the genetic algorithm. Computational Economics 13 (3), 201–209.

Zhang, M., Sexton, R. J., 2001. Fob or uniform delivered prices: Strategic choice and welfare effects. Journal of Industrial Economics 49 (2), 197–221.